CONTROLLABLE IMAGE ILLUMINATION ENHANCEMENT WITH AN OVER-ENHANCEMENT MEASURE

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ABSTRACT

The quality of images or videos that suffer from exposure distortions can be enhanced using histogram equalization or retinex methods. However, the relationship between the visual quality and the degree of enhancement is an inverted U-shaped function with a peak point, and many existing methods have parameters that have no clear relationship with image quality. We introduce a controllable illumination enhancement system, where the degree of enhancement can be adjusted using a single parameter. We then propose an over-enhancement measure, Lightness Order Measure (LOM), which quantifies the unnaturalness based on a local inversion of lightness order. We explore the relationship between the peak point and LOM in a subjective test. The results indicate that LOM reduces content dependency compared to existing methods. Our subjective test also evaluates the image quality of our enhancement, and demonstrates the effectiveness of our method.

***Index Terms*—** image enhancement, illumination, over-enhancement, image quality, subjective test

1. INTRODUCTION

Images or videos suffer from exposure distortions when the camera sensor is not exposed to the proper amount of light [1]. Exposure distortions are often caused by bad environmental lighting or bad capture angles, which are often spatially inconsistent within an image. To improve the quality of images with exposure distortions, many different types of enhancement methods [2–4] have been proposed and widely used to edit the illumination within an image.

This relationship between enhancement and image visual quality can be described as a concave function with a peak point. We consider the peak point as the optimal degree of enhancement, defined as the optimal point (OP). The concave relationship is produced by three aspects, contrast, exposure level and newly generated artifacts introduced by enhancement operations. First, image quality is a concave function of contrast. According to the results from image quality database TID2013 [5], when the synthetic contrast manipulation is applied to an image, there exists a peak point of quality corresponding to its best contrast. Second, the exposure level change also has a concave relationship with image quality [1], and its best point corresponds to the exposure level at which the image is well-exposed, not either under-exposed or over-exposed. Third, enhancement operations often generate new artifacts, such as color shift or loss, noise amplification, structure modification or unnaturalness [6]. The combined visual effect of newly generated artifacts and contrast change can also be described as a concave function of image quality.

The concave function of enhancement is content dependent, in that the OP varies for different content. One unsolved problem is how to define the OP for different images and characterize the concave function. Our solution is to enhance the image different amounts, and then characterize the concave curve including the OP using a content-independent over-enhancement measure.

To investigate the concave relationship and to define the OP of enhancement, we select First-Person images or video frames captured by wearable cameras as our image sources in this paper. See Figure 1 for examples. These images cover a wide range of amount of exposure distortions captured in different environments, and contain other types of quality degradations simultaneously [7, 8].

In this paper, we propose a controllable illumination enhancement method for which the degree of enhancement can be adjusted using a single parameter. Many existing enhancement methods including histogram equalization [2, 9], retinex methods [3, 4] and others [10–13] have no clear relationship between their parameters and image quality. However, our single parameter has a concave relationship with image quality. In our method, we model under-exposure and over-exposure differently to assign under-exposed and over-exposed probabilities for each pixel. We then design a system that applies logarithmic mapping in the identified under-exposed pixels with boundary-artifact compensation. Our mapping uses the assigned under-exposed probabilities, the artifact compensation weights and the single adjustment parameter together to calculate mapping coefficients. We also propose an over-enhancement measure, Lightness Order Measure (LOM) to quantify the unnaturalness in the enhanced image. We consider the unnaturalness to be related to the inversion of relative lightness order between neighboring pixels, and which is influenced by both the proportion of inversions and the inversion magnitude.

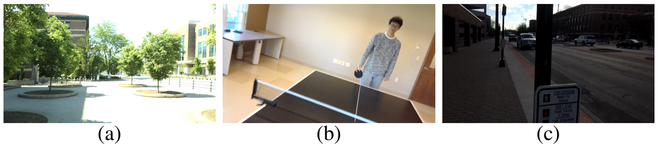

Fig. 1: First-Person images with exposure distortions

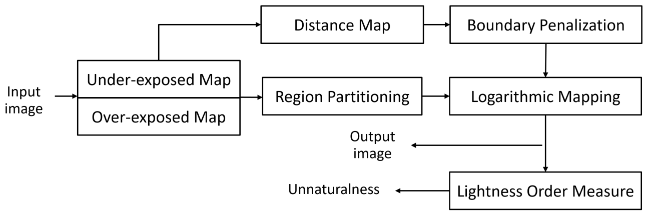

Fig. 2: Illumination enhancement block diagram

In Section 2, we describe and illustrate the three major parts in our system of controllable illumination enhancement: under-exposed map and over-exposed map, boundary penalization, logarithmic mapping. We then illustrate our proposed over-enhancement measure, LOM, in Section 3. Section 4 implements a subjective test to explore the relationship between LOM and image subjective quality after enhancement, and demonstrates the effectiveness of LOM and our illumination enhancement method.

2. CONTROLLABLE ILLUMINATION ENHANCEMENT

In this section, we propose a controllable illumination enhancement method that allows a single parameter to adjust the degree of enhancement. Our enhancement system has 3 major parts: under-exposure and over-exposure map, boundary penalization and logarithmic mapping. We separately model the under-exposed and over-exposed map based on an over-exposure model in [10]. Our logarithmic mapping takes into account the under-exposed map values and boundary-artifact compensation weights, and the single adjustment parameter β to assign mapping coefficients for each pixel.

Figure 2 shows the block diagram of our method. First, an under-exposed map and an over-exposed map are calculated for the input image. Then, the image is partitioned into either under-exposed or over-exposed regions. Third, a logarithmic mapping is applied to the under-exposed regions with penalization to compensate for the boundary artifacts. Finally, our proposed Lightness Order Measure (LOM) quantifies the unnaturalness of the output image, illustrated in Section 3. Details for each step are explained next.

Under-exposed map and Over-exposed map: We create an under-exposed map and an over-exposed map separately for an image considering both pixel saturation and intensity. Pixel saturation is affected similarly by both under-exposure and over-exposure, in that low saturation pixels are perceived to be close to gray, and therefore are indistinguishable from each other [14]. A well-exposed pixel, on the other hand, has color that can be correctly perceived. However, pixel intensity is affected differently. Over-exposed pixels often have high intensity, while under-exposed pixels have low intensity.

Based on the over-exposure detection model proposed in [10], we model both the under-exposed map M_u and the over-exposed map M_o in $L^*a^*b^*$ space as

$$M_u = 0.5 \tanh\left(\delta(L_{ut} - (\sqrt{a^2+b^2} + G(L)))\right) + 0.5 \quad (1)$$

$$M_o = 0.5 \tanh\left(\delta(L_{ot} - (\sqrt{a^2+b^2} - G(L)))\right) + 0.5 \quad (2)$$

where L, a and b are rescaled pixel values (from 0 to 255) of L*, a* and b*. For a fixed L, when saturation drops, $\sqrt{a^2+b^2}$ will decrease. $G(\cdot)$ is a 15×15 Gaussian filter with $\sigma = 3$. The range of M_u and M_o is from 0 to 1, corresponding to the probability of a pixel to be under-exposed or over-exposed, respectively. We set $L_{ut} = 255$ and $L_{ot} = 0$ so that M_u and M_o are both 0.5 when the pixel has intensity and saturation that are half of their entire range. δ controls how fast M_u and M_o increase or decrease with L or $\sqrt{a^2+b^2}$, and is experimentally set to be 1/60. Figure 3 shows an example image with its under-exposed map and over-exposed map.

Boundary penalization: The image is partitioned into under-exposed regions R_u ($M_u > M_o$) and over-exposed regions R_o ($M_u < M_o$). To eliminate the artifacts near the boundary of R_u and R_o after enhancement, we introduce a boundary penalization weighting function $\omega(x, y)$, where (x, y) is pixel location. We first compute the Euclidean distance between pixels to its closest partitioning edges between R_o and R_u, and normalize it to get distance map $\mathcal{D}$. Then $\omega(x, y)$ is calculated as

$$\omega(x,y) = \frac{\log(\mathcal{D}(x,y)(p-1)+1)}{\log(p)}, \quad (3)$$

where p is a constant, and experimentally set to be 10.

Logarithmic mapping: To enhance the illumination of the under-exposed regions, we use the logarithm mapping function

$$L'(x,y) = \frac{\log(L(x,y) * (\gamma(x,y) - 1) + 1)}{\log(\gamma(x,y))}, \quad (4)$$

where $L'(x, y)$ and $L(x, y)$ are luminance values in $L^*a^*b^*$ space for the enhanced image and the original image, respectively. $\gamma(x, y)$ is the mapping coefficient, calculated as

$$\gamma(x,y) = 1 + M_u(x,y) * \omega(x,y) * \beta, \quad (5)$$

where β is the control parameter that can adjust the amount of enhancement. We finally convert the image back to RGB space using the mapped luminance L' and original a^*, b^*. Figure 4 shows an example image, extracted from video "Alin, Day1" in [15], enhanced to 7 different amounts by adjusting β.

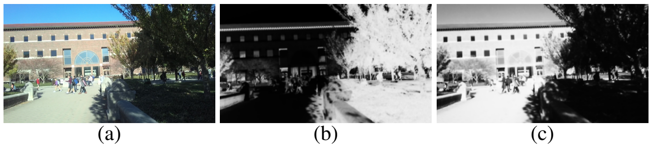

Fig. 3: (a) original image (b) under-exposed map M_u (c) over-exposed map M_o

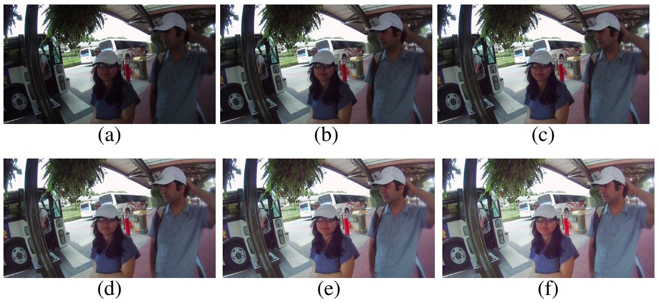

Fig. 4: (a) original image (b) $\beta = 2$ (c) $\beta = 4$ (d) $\beta = 8$ (e) $\beta = 16$ (f) $\beta = 24$

3. OVER-ENHANCEMENT MEASURE

In this section, we propose an over-enhancement measure, the Lightness Order Measure (LOM), to quantify the unnaturalness after enhancement, and we compare it with two existing metrics, SMO [16] and LOE [17].

The principle of our Lightness Order Measure (LOM) is to measure when the *relative* lightness order of pixels in the image is reversed. Relative Lightness order [17] refers to the pixel intensity order of the image, represented as $I(x_1, y_1) > I(x_2, y_2)$, where (x_1, y_1) and (x_2, y_2) are two different pixel locations. The relative lightness order of an image should be preserved to keep its naturalness.

There are two existing over-enhancement measures, SMO and LOE. SMO measures the image structure change; it quantifies the difference of gradients, standard deviation and entropy between the original image and the enhanced image. LOE measures the change of lightness order globally in the image; it compares every two pixels and calculates how many pairs are reversed. All three measures compare the original image to the enhanced image.

LOM shows advantages compared to SMO and LOE. Compared to SMO, LOM does not use content-dependent information, so it is subject to less influence from different contents. Compared to LOE, LOM considers the relative lightness order locally and quantifies the magnitude of the inversion; hence it improves the computational efficiency.

To compute LOM, let the original image be i_1 and the enhanced image be i_2 in luminance domain. First, the local mean filter is both applied to i_1 and i_2 with window size 31×31, and the filtered luminance images are f_1 and f_2, respectively. Second, we calculate the difference image $d_1 = f_1 - i_1$ and $d_2 = f_2 - i_2$. Third, we quantify the LOM as

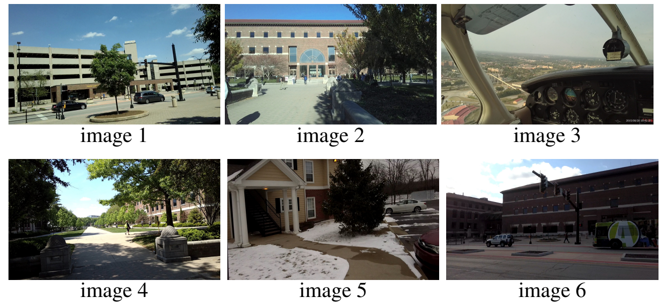

Fig. 5: Test images: (1) $P_u = 0.35$ (2) $P_u = 0.57$ (3) $P_u = 0.58$ (4) $P_u = 0.76$ (5) $P_u = 0.76$ (6) $P_u = 0.82$

$$\begin{aligned} LOM = \frac{1}{H \cdot W} \sum_x \sum_y \big| (d_2(x,y) - d_1(x,y)) \\ \cdot \frac{sign(d_2(x,y)) - sign(d_1(x,y))}{2} \big|, \end{aligned} \tag{6}$$

where H and W are image height and width. Larger values for LOM indicate greater unnaturalness.

4. EXPERIMENTS AND RESULTS

In this section, we implement a subjective test with two phases. The first phase explores subjective quality of enhanced images with different values of LOM. It also assesses the performance LOM, SMO and LOE to characterize the OP of the concave quality curve for different contents. The second phase evaluates the subjective quality of images enhanced by prior existing methods and ours. Both phases are used to test the effectiveness of our enhancement method with over-enhancement measure, LOM.

Test sources are 6 video frames captured by a wearable camera Pivothead (1080p30fps), shown in Figure 5. The test images are ordered using the percentage of partitioned under-exposed regions P_u. Each test image is enhanced by our proposed method using 9 different values of β, and by five existing enhancement methods, LDR [18], CVC [19], WAHE [9], SRIE [4], Low-light enhancement using camera response model (LLCRM) [20]. Examples of enhanced images using five methods and ours are shown in Figure 6, where the original image is 6 in Figure 5.

The subjective test has two phases. The first phase finds the best enhanced image for a given content from a set of 9 versions enhanced with different β. The second phase uses the best enhanced image found in the first phase to compare five existing enhancement methods with ours.

Our test method is paired comparison. Each pair of enhanced images of the same content is presented side by side on a 4k monitor (DELL P2415Q), and the right-side image is horizontally flipped. The monitor resolution is 3840×2160. The image is symmetrically cropped to be 1900×1080. Each of the 20 subjects are asked to indicate *which image is perceptually better in terms of illumination, noise, naturalness, color*

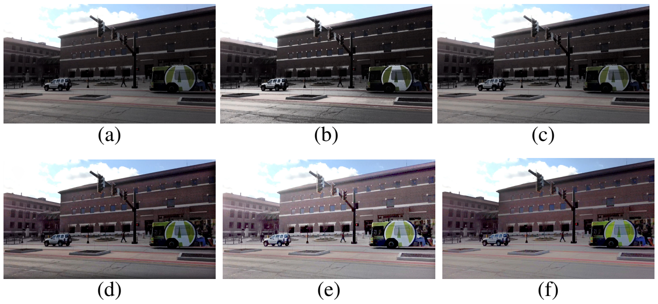

Fig. 6: Example enhanced images: (a) LDR (b) CVC (c) WAHE (d) SRIE (e) LLCRM (f) ours

and incorrect textures. The subjective image quality is calculated from the paired comparison results using the Bradley-Terry Model [21]. The calculated subjective scores are all relative; the best quality score is set to be 0.

The results in Figure 7 show that each of LOM, SMO and LOE has a concave relationship with subjective image quality, and the concave curve varies for different contents. The comparison between Figure 7(a), 7(b) and 7(c) indicates that our LOM reduces content-dependency compared to SMO and LOE. The overlap between concave curves of different contents in Figure 7(a) is much greater than in Figure 7(b) and (c). For example in Figure 7(b), the best version of image 6 has an SMO of 5.5, but this is larger than the SMO of all versions of the other 5 images, including their worst quality versions. In Figure 7(c), the comparisons between the best version of image 5 with LOE 440 and images 2, 3, 4, 6, and between the best version of image 6 with LOE 358 and images 2, 4 show the same situations as mentioned for Figure 7(b). This means SMO and LOE are unsuited for use to find the best degree of enhancement when applied to different contents. In contrast, Figure 7(a) shows a better set of concave curves; the LOM of all versions of one image are neither smaller or larger than the LOM value of the best version of another image.

Visual quality of an enhanced image is influenced by both illumination and naturalness. For example, image 6 has the highest P_u and its best version has the largest LOM compared to the other 5. The reason is that image 6 is heavily under-exposed, so the illumination improvement has a larger influence than unnaturalness.

Table I shows the results of subjective quality of images enhanced by the five enhancement methods and ours, and indicates that our method shows more balanced performance considering image quality and computational efficiency. The results of subjective scores show that the overall performance of the 6 methods can be listed from the best to the worst as SRIE, ours, WAHE, LDR, CVC, LLCRM. LLCRM is applied for low-light image enhancement, so it performs much worse when P_u is small for images 1 to 4 compared to other methods. LDR, CVC and WAHE focus on contrast enhancement, they all have relatively unbalanced performance compared to SRIE and ours. For example, their performance is worse for image 6 with $P_u = 0.82$ than images 1, 2, 3 with $P_u < 0.6$.

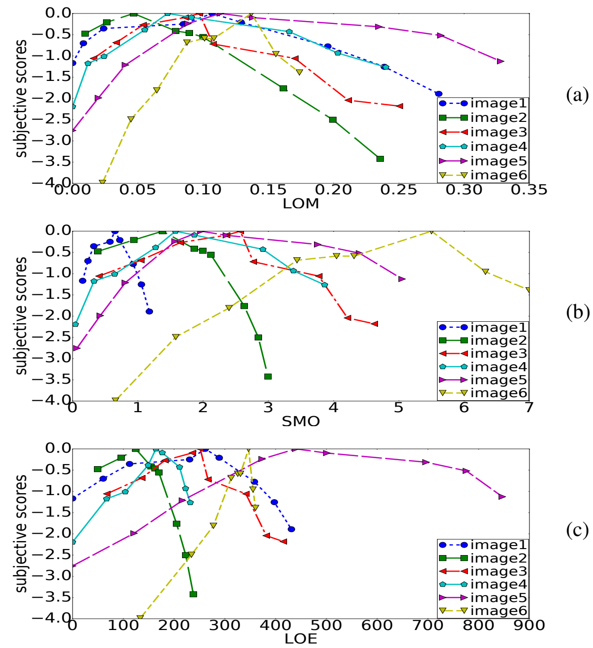

Fig. 7: Subjective quality of enhanced images with (a) LOM (b) SMO (c) LOE

image	LDR	CVC	WAHE	SRIE	LLCRM	ours
1	0.68	0.28	0.68	0	2.37	0.44
2	0.82	0.95	0	0.13	3.95	0.39
3	1.45	0.69	1.75	0	2.78	0.51
4	1.91	1.15	1.23	0.47	2.54	0
5	1.05	1.65	2.19	0	0.53	1.01
6	3.00	3.65	2.46	0.73	2.18	0
time(s)	0.42	4.88	0.41	89.84	1.74	1.81

Table I: Negative subjective quality ("0" indicates the best) and average processing time of the 6 enhancement methods

SRIE and our method show the best or at least the 3rd performance for different contents. However, the processing time for SRIE is more than 50 times longer than the other five methods. Because SRIE uses an iterative optimization strategy, and the optimization time significantly depends on the content. Overall, the performance of our method is more balanced for contents that cover a range of P_u from 0.35 to 0.82.

5. CONCLUSIONS

In this paper, we propose a controllable enhancement illumination method that allows the degree of enhancement to be adjusted using a single parameter. We then propose an over-enhancement measure, LOM, to evaluate the unnaturalness of enhanced images. Our results of subjective test indicates the effectiveness of our enhancement method and LOM. Remaining issues for future work are how to improve the illumination within over-exposed regions simultaneously and how to design an objective measure for image quality after enhancement that provides a consistent evaluation for both different contents and enhancement methods [6].

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